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Application of Discrete-Event Simulation in Health Care: a Review

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List of abbreviations

CART	Classification and Regression Tree
CBA	Coordinated Booked Admission
CPS	Care Pathway Simulator
DES	Discrete-Event Simulation
ED	Emergency Department
ENT	Ear, Nose and Throat
GDP	Gross Domestic Product
ICU	Intensive Care Unit
LoS	Length of Stay
QALY	Quality-Adjusted Life-Year
QNA	Queuing Network Analysis
MAU	Medical Assessment Unit
MRU	Maximum Resource Use
NHS	National Health Service
OOP	Object Oriented Paradigm
TQM	Total Quality Management
UBA	Uncoordinated Booked Admission
VSE	Visual Simulation Environment
ZWT	Zero Waiting Time

ABSTRACT

The acceptance of applying process simulation in health care has significantly increased during the last decade, leading to an increase of publication in this area. Health care managers and researchers that are attracted by the idea of applying simulation in their field, desire to view methodologies and results of different simulation projects, yet may be overstrained by the large volume of the diverse literature. Thus, this paper, structured as a quick reference guide, presents a comprehensive review of process simulation applications in healthcare areas, which summarises projects applied in health care facilities like hospitals, emergency departments, intensive care units, surgical procedures, outpatient clinics, and facilities allocated in the health care supply chain. Additionally the provision of health in economic simulation models is covered within this review. Seventy articles are reviewed covering a range of the last decade that present the potential of simulation as a strategic competitive tool for decision makers in the aforementioned areas. Challenges to implement simulation results into existing systems are also discussed.

1. Introduction

Ageing and growing population cause a steadily increase in total costs for health care. An increase of about one per cent every fifth year of the fraction of health care costs of the GPD is observed in the developed countries (WHO, 2008). Within the Euro zone, for example, 9 per cent of the GDP is already spent on health in the year 2007. In order to slow down this trend, health care professionals and researchers are obliged to find new methodologies to manage operations in health care and the provision of health efficiently. To accomplish this, solutions are derived and applied from the area of operations research. Simulation - widely accepted and already applied in manufacturing, military, and logistics – showed great potential to be accepted in health care facilities. Simulation, in this paper referred as a term for process simulation, became an attractive tool due to its flexible approach, enabling the replication of the behaviour of health care facilities in the desired level of detail in terms of models. These models reflect the current state of the facility during runtime and the flow of the patients through the system allowing investigations on key performance measures like lengths of stay (LoS), waiting times, queue size, and utilisation - necessary for benchmarks leading to performance comparisons. A major feature is the capability to test scenarios, commonly referred as 'What-If'-questions, without disrupting the running system. Another important feature is consideration of uncertainty and variability by the facile integration of stochastic into the model. Simulation benefits by these features and thus advances to a valuable tool for decision makers. Its flexibility to integrate other solution techniques, like those derived from operations research or general optimisation strategies, enhanced simulation as an attractive approach for solving operations problems in uncertain and complex environments. Health care would be such a domain - its first mission: provide health, but its demand is random and versatile. Uncertainty and complexity is the daily burden of hospital managers or clinic administrators, but simulation thus empowers them to investigate the consequences of possible changes in clinic without disrupting the running system or occupying any of its resources. One major disadvantage is that generating a simulation model can be a time consuming process, demanding for an in depth analysis of the system. However, the gained understanding gives the manger an additional degree of control of and credibility in this virtual model.

Simulation is applicable to a wide range of the health care sectors like for example doctor's practice, outpatient clinics, hospitals and even models for demographical provision of health. These diverse sectors offer a wide versatility of simulation projects. It can be observed that the publication rate of simulation papers relating to the health care sector has doubled within the last decade. Focusing on the same time interval for the last four decades between 2003 and 2007 sixty-two publications are identified while between 1993 and 1997 twenty eight publications were published and between 1973 and 1977 only eight (Figure 1) (Jun et al., 1999). This paper offers a comprehensive reference work of the publications from 1995 to 2008, which groups the publications into the application fields and gives a brief summary on the background, application, methodology applied, and conclusions for each of the seventy referenced papers. Table 1 offers a quick overview on the authors who published in which health care sector and additionally indicates whether the results of the simulation studies are mentioned to be implemented in the certain facility. This paper focuses on a selection of seventy previous simulations; for a review of additional studies one of the preceding review papers can be consulted.

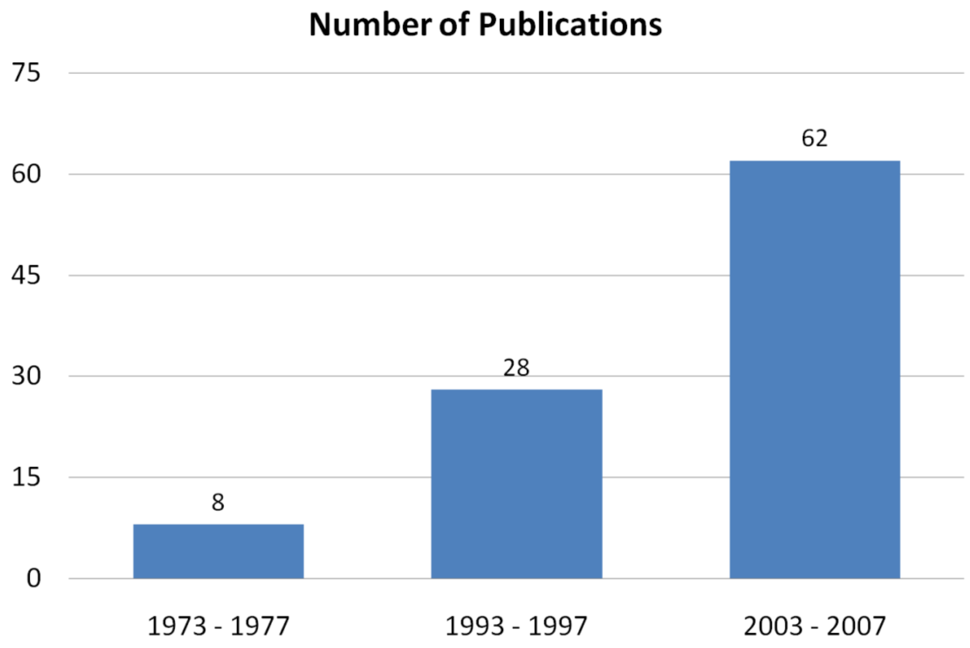

Figure 1: Number of publications of simulation applied in health care within different periods

A comprehensive, often cited review is given by Jun et al. (1999), who references 117 articles which were published between 1952 and 1997. This paper refers to previous research on single or multi-facility health care clinics, summarises articles written on different topics like patient flow, allocation of resources, and gives an outlook on future directions. Preater (2002) focuses on queues in health care with a grouped bibliography (Preater, 2001) such as appointments, outpatients and waiting lists, departments, compartmental modelling, ambulances, and miscellaneous. Another focused review is given by Cayirli and Veral, (2003). Their review concentrates on outpatient scheduling in health care and divides the topic into its elements and methodologies. Here simulation is mentioned only as a side topic as a viable solution technique. A very systematic and focused review is given by (Fone et al., 2003) which describes a survey of articles on the use and value of computer simulation modelling applied in health care. This survey uses data which results from automated queries on certain keywords of 60 articles in various literature databases. Another survey and discussion paper is published by (Eldabi et al., 2007) in which the authors conclude that simulation with its flexibility has advanced to a single-solution-based method to solve problems in health care. Limitations and boundaries of the term simulation can be found in Streufert et al.'s (2001) overview paper, which offers a good overview of simulation projects applied in health care. Various references for simulation projects on large scale emergencies are cited by Jia et al. (2007), who also present a modelling approach to provide communities with emergency care in an catastrophic event.

This review follows the structure suggested by Jun et al. (1999), which achieved a high number of citations due to its comprehensiveness. By September 2008, 118 citations are counted by Google scholar. Even though the structure and the detail of the reviewed paper is setting an example, this paper will not fully align with the structure of our predecessors due to the focus on the application fields like hospital, emergency departments (ED), outpatient clinics, demographic health provision, and health care supply chain environment. This review – conceptualized as a quick reference guide - allows tracing which project has been applied in which sector (Table 1). After reviewing the projects applied in healthcare during the last decade, a conclusion on the reviewed papers is provided.

2. Main application categories for simulation in the health sector

Simulation is applied to projects which can be classified into five categories corresponding to their application fields: hospitals, surgeries, intensive care units (ICU), specialties, EDs, outpatient clinics, demographic health provision and health care supply chain environment Hospitals, as dominant resulting health care provider, is the first category followed by EDs, which can be argued to be a subset of the hospital, but due to its high random demand compared to hospitals in general, papers are investigated separately. The next review category is outpatient clinics, followed by the review of demographic health care provision models, like the estimation of public treatment costs, transplant policies or the provision of health care for a region or local community, where several networked facilities interact. The last category is the health care supply chain environment, which delivers goods or services for those who provide health care and thus share common features like the uncertainty of demand and limited resources. Figure 2 and Figure 3 offer an overview of the number of publication for each sector and field.

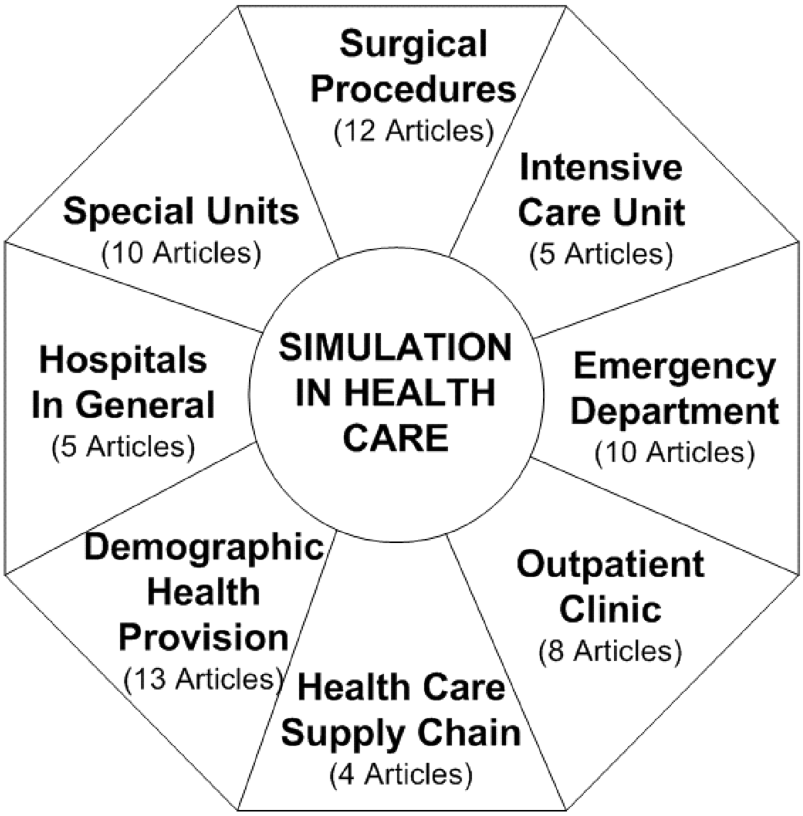

Figure 2: Sections and the corresponding number of investigated articles

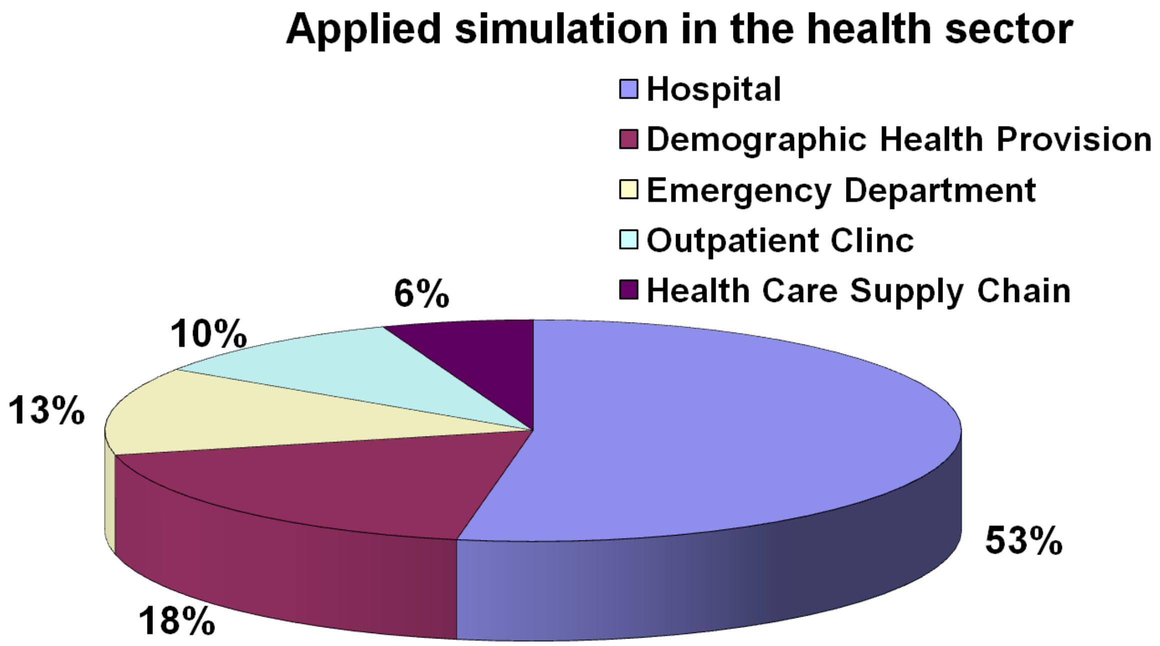

Figure 3: Distribution of simulation applied in health care sector

2.1 Simulation applied in hospitals

Publicly funded acute hospitals are a large cost factor to the economy, with about a third of the health care expenditure being dedicated to them (Cochran and Bharti, 2006b). Yet, hospitals fulfill a key role in the provision of health: dependent on size and mission, they comprise several units to provide general health care, diagnostics, treatments, and medical care. Among several others the main units are surgeries, ICUs, and EDs. Beside its primary treatment and care mission, the hospital has to ensure the hospitality for their patients, which includes the accommodation and catering of the patient. As hospital beds are essential for the accommodation of patients, the size of hospitals is indicated by the number of beds provided. The hospital bed itself is treated as a cost factor within the hospital, although the actual cost factor is the treatment. From the perspective of process flow modelling, the number of hospital beds is thus a key element when it comes to analysing and forecasting capacity. Despite capacity planning efforts, a surplus of demand, leading to an increase in waiting lists, is sometimes inevitable. The longer the waiting lists, the less the provision of necessary treatment can be guaranteed to the local community. The ideal for the patient would be no waiting for a treatment; this however would result in low occupancy rates and in high costs for the care provider. Finding the optimum trade off between capacity usage and patient demand is a crucial task for the health care provider.

Table 1: Listing corresponding authors to each section, also including an indication whether the simulation results are implemented

Sector	Authors	Implemented
Hospital	Vissers (1998), Rohleder and Klassen (2002), Sundaramoorthi et al. (2006)[USA], Gutjahr and Rauner (2007)[Austria], Vissers et al. (2007)	N
	Moreno et al. (1999)[Spain], Harper (2002), Cochran and Barti (2006b)[USA]	Y
Surgery	McAleer et al. (1995), Dexter et al.(1999)[USA], Bowers and Mould (2002)[UK], Everett (2002), Tyler et al. (2003)[USA], Bowers and Mould (2004)[UK], Sciomachen et al. (2005)[Italy], Jebali et al. (2006), Cardoen and Demeulemeester (2007)[Netherlands], Lehtonen et al. (2007)[Finland], Vasilakis et al. (2007), Lamiri et al. (2008)	N
Intensive Care Unit	Ridge et al. (1998), Kim et al. (1999)[China], Kim et al. (2000), Kim and Horowitz (2002)[China], Litvak et al. (2008)[Netherlands]	N
Special Units	El-Darzi et al. (1998)[UK], Groothuis et al. (2001)[Netherlands], Swisher and Jacobson (2002), Utley et al. (2003)[UK], Bowers and Mould (2005)[UK], Green et al. (2006), Cardoen and Demeulemeester (2007)[Netherlands], Oddoye et al. (2009)[UK]	N
	Cochran and Bharti (2006a)[USA], Elkhuizen et al. (2007)	Y
Emergency Department	Gonzalez et al. (1997)[Puerto Rico], Bagust et al. (1999)[UK], Lane et al. (2000)[UK], Sinreich and Marmor (2004)[Israel], Ashton et al. (2005)[UK], Martinez-Garcia and Mendez-Olague (2005)[Mexico], Hoot et al. (2008)	N
	Blake and Carter (1996)[Canada], Kuban Altınel and Ulaş (1996)[Turkey], Yeh and Lin (2007)[Taiwan]	Y
Outpatient Clincs	Swisher et al. (2001)[USA], De Angelis et al. (2003), Robinson and Chen (2003), Wijewickrama (2006)[Japan]	N
	Huarng and Lee (1996)[Taiwan], Harper and Gamlin (2003)[UK], Dodds (2005)[UK], Rohleder et al. (2007)[Canada]	Y
Demographic Health Provision	Ratcliffe et al. (2001), Pasin et al. (2002)[Canada], Brailsford and Schmidt (2003)[UK], Davies et al. (2003)[China], Harper et al. (2003)[India], Roderick et al. (2004)[UK], Katsaliaki et al. (2005), Paul et al. (2006)	N
	Chu and Chu (2000)[China], Vasilakis and El-Darzi (2001)[UK], Harper and Shahani (2003)[India], Rauner and Bajmoczy (2003)[Austria], Brailsford et al. (2004)[UK]	Y
Health Care Supply Chain	Wijewickrama (2004)[Japan]	N
	Couchman et al. (2002)[UK], Chu et al. (2003)[China], Haijema et al. (2007)[Netherlands]	Y

2.1.1 Review of simulation applied in hospitals

In the following simulation project, the authors identified that up to 2002 it was common to estimate the capacity requirements for hospital beds using the average length of stay (LoS) figures in the Royal Berkshire and Battle Hospitals NHS Trust in Reading. In order to support the hospital management in their decisions on bed usage and patient flow, a tool based on simulation is designed which uses several programs such as the simulation shell - TOCHSIM and the data collection tool - Apollo. The designed simulation tool allows a more accurate interpretation of the current usage of the hospital resources which is achieved by a flow model of the patient routing through the whole hierarchy of the hospital. Scenarios are used to illustrate the consequences of possible decisions by the hospital management. It is shown that the previous LoS estimates mislead in the interpretation of the current capacity situation. Instead, applying the tool allows forecasting future bed requirements, categorizing of patients, and quantifying of the effects of combining specialty bed-pools depicts capacity simulations more accurately. In addition, using this simulation tool enables forecasting the effect of a change in admission policy and hospital extension (Harper et al., 2002).

Balancing patient demand of a large comprehensive hospital in the south-western USA with more than 400 hospital beds, is a challenge which has been taken by Cochran and Barti (2006b). A queuing network analysis (QNA) is combined with a discrete-event-simulation (DES) that enables a balancing of bed utilisation. Experts are consulted and data extracted from the hospital database management system to form the basis for the model. The QNA identifies the bottlenecks within the system, which are widened by reallocating resources. Their study supports an extended description of verification and validation approaches that explain how DES is used to verify results. The implementation of the case study results in a 8 per cent increase in patient flow and a significant improvement of peak behaviour is demonstrated in smoothed demand (Cochran and Bharti, 2006b).

Another case study on patient flow and allocation of resources within a general hospital is been conducted by Vissers (1998). Until then, the hospital management of the certain hospital applied estimates from previous assumptions in order to manage the utilisation of resources. Vissers (1998), instead, uses a mathematical approach for the patient flow and builds a resource model. Patient records are extracted from the hospital database and are integrated in these models, which are validated with a detailed sensitivity analysis. The case study results in a comprehensive decision aid for either the reallocation of resources or the reduction of LoS. It is concluded with the description of the “Time-phased Resource Allocation” method which considers the right level of allocations with the right balance between allocations of different resources, avoiding capacity loss, as well as the correct timing, avoiding unnecessary peaks and troughs (Vissers, 1998).

As large scale simulation models may become quite unmanageable, as Moreno et al. (1999) observes when studying a whole hospital complex located in De la Candelaria, Tenerife, a divide and conquer design methodology is used in order to develop a micro and macro model of the hospital on a patient flow basis. With this approach the target is to indentify and eliminate bottlenecks. The laboratory service is identified as such and eliminated by adding ten more sessions. These simulation results are implemented and the simulation model itself is used as a decision support tool for further assistance to the management (Moreno et al., 1999).

A more general study, which is applied to a general hospital, is recommended as a framework to other modellers. The benefits of the suggested framework are the development of a detailed integrated simulation tools for the planning and management of hospital beds, operating theatres and workforce needs (Harper, 2002).To reflect the hospital dynamics, a flow model based on continuous modelling is chosen whereas the input for the model is classified by using the CART regression tree analysis, which allows a categorized and therefore detailed view on the patient records. Overall the framework illustrates the issues for modelling health care facilities. The case study which is used to demonstrate the benefits of this framework may lead to a flattened occupancy rate, which utilizes a 2 per cent higher patient throughput and a drop of the overall surgery refusal rate from 5 to 3 per cent (Harper, 2002). The results of this study are implemented in practice.

As important as the optimum resource allocation in hospital is, the optimum staff utilisation, which is addressed by Gutjahr and Rauner (2007) who compare the Greedy algorithm with the ant colony optimisation approach. This case study is undertaken in a hospital in Vienna and uses values derived by a DES, which is developed for this comparison. The DES includes a general cost function which is used for the optimisation. Analysing the optimisation results it can be seen, that the ant colony optimisation achieves a additional cost saving of between 1 and 4 per cent compared to the Greedy algorithm (Gutjahr and Rauner, 2007).

A novel nurse - patient assignment programme is developed on the basis of the data provided by Baylor Medical Center at Grapevine TX and Patricia Turpin. Sundaramoorthi et al., (2006) apply a stochastic simulation model (SIMNA) which is combined with a CART regression tree analysis to determine the transition probabilities for nurse movements to predict the amount of time spent at a certain location. To support their findings validation is applied and the 40-20-40-rule is referenced (McKay et al., 1986), which suggests that a modeller should spent 40 per cent of the time with data analysis, 20 per cent with the transition and 40 per cent with the implementation of the model. This assignment programme assists nurses to make better decisions on nurse - patient assignments for a work shift, which results in a better care for patients, balanced workloads for nurses, and cost savings for the whole hospital (Sundaramoorthi et al., 2006).

Continuing with assignment tools, Vissers et al., (2007) introduce a platform which compares the performance of admission systems for hospitals. This theoretical model is built on assumptions and assumes a simplified hospital. The following admission plans are investigated: Maximum Resource Use (MRU), Zero Waiting Time (ZWT), Coordinated Booked Admission (CBA), and Uncoordinated Booked Admission (UBA). These different admission plans are then evaluated according to the resource utilisation of beds, intensive care beds, operating theatres, and nursing staff. Finally the paper proposes a contingency perspective to identify the most suitable admission strategy (Vissers et al., 2007).

Another assignment issue is concerned with the fluctuating demand loads in a rolling - horizon environment by applying overload rules and rule delay (Rohleder and Klassen, 2002). Management chooses between the following overload rules: pure overtime, double booking from first to last or from the last to the first, double booking every fifth slot. The overbooking rules are combinable with the three rule delay options: simply none, or the 1 and 2 day delay. The combined rules with the overload options identify the best mix of rules. It is emphasised that the application of these results depends strongly on hospital idiosyncrasies and the patient demand. This paper identifies methods for minimizing client waiting and server idleness which are of significant value to practitioners.

Reviewing the previous papers on bed capacity management, it can be shown that simulation has the potential to significantly improve service delivery with only minor changes in the resource parameter. In the above cases DES was complemented with various scheduling algorithms in order to compare results in an illustrative manner.

2.1.2 Review of simulation studies in surgical procedures in hospitals

Surgical procedures are one of the main components of hospital activity. Surgical procedures are applied on patients waiting in wards or ICU, and are released to the recovery area, from where patients are directed to the ward or ICU, where patients need intensive care or treatment. The operating room is therefore a core process which impacts on the whole hospital, as bed capacity for example is also required for medical care, which would not result in surgical operation. Focusing on the general flow perspective, scarce human and physical resources for surgical procedures have to be allocated in an optimum trade off in order to empower the hospital to operate efficiently. Many solution techniques are possible to find the optimum work load, but primarily solution techniques centre on optimising the schedule in uncertain demand environments and / or optimising the patient flow, for example, by eliminating unnecessary waits between surgeries caused by occupied recovery areas. In this area simulation is credited as an attractive approach in finding solutions due to the possibility of combining DES with several other solution techniques. Different scheduling policies can be investigated on their impact, or the integration of optimisation strategies is also feasible to find the optimum utilisation.

A study is undertaken by McAleer et al. (1995), which investigates a multi theatre suite by applying an entity life cycle diagram with data derived from the hospital records, covering the time span of four “regular” weeks. The expertise of the staff is consulted in order to validate the model. Common complaints by surgeons about the understaffing of porters are shown to be incorrect once the first results are retrieved. Other results suggest that the capacity of the recovery area should be increased, which allows the six –suite theatre block to operate with a minimum of time delays between procedures (McAleer et al., 1995).

An investigational study which incorporates the high uncertainty and variability of patient demand is undertaken at a typical hospital of the UK by Bowers and Mould (2004). A simple Monte Carlo simulation including the patient demand model is used to emulate the orthopaedic trauma theatre. The use of simulation showed that the scheduling of the trauma theatres is modified by accepting a higher risk of cancellation, which frees two additional surgery hours per week. These results are applied to a general hospital in the UK increases the overall performance by 13 per cent per year on elective surgeries (Bowers and Mould, 2004). These findings are published in a technical manner in the European Journal of Operations Research (Bowers and Mould, 2004), while health care management issues as well as implementation barriers are addressed in an article published in the Journal of Management in Medicine (Bowers and Mould, 2002).

Cardoen and Demeulemeester, (2007) present a project of which uses integrated patient care pathways to derive the simulation model. The project is dedicated to two case studies, the first in the Middleheim hospital in Antwerp which investigates the consultation and surgery unit of the hospital, the second in the catheterization facility of the university hospital of Gasthuisberg. The use of integrated care pathways eases the development of the simulation models because the path of the patient is already well documented and relatively easy to derive and to integrate in a simulation model. Integrating these paths in a simulation model guarantees that the model replicates the behaviour of the clinic. Investigation on the model shows the effects of the changes in the bed capacity to bed utilisation. In this particular study unused bed capacity is freed due to the findings of the simulation model (Cardoen and Demeulemeester, 2007).

Another approach to optimize the utilisation of operating theatres is to apply mixed integer programming in order to streamline surgery sequences efficiently, achieved by balancing the scheduled blocks. The model includes constraints and tests 25 different scenarios in order to find the best utilisation. The authors highlight that further research should include the priority of the patients depending on their state of severity and the priority preferences of the surgeons (Jebali et al., 2006).

A different theoretical study used mixed integer programming, which is integrated in a Monte Carlo simulation (cf. Lamiri et al., (2008)). The elective and emergency demand for surgical procedures are considered in the model to precisely reflect the variations in demand for the surgery. As an alternative optimisation strategy it is also proposed to combine this model with simulated annealing, taboo search, or genetic algorithm. However, proposing this methodology achieves a cost reduction of 4 per cent (Lamiri et al., 2008).

The following project study focuses on applying a straight forward discrete-event simulation which considers the urgency of treating the patients. This model can be used as a twofold operational tool, first to match hospital availability, and second to consider the patient needs. Expertise of the medical staff has been consulted to verify the accurateness of the model. This study focuses on the benefits of DES when applied in hospital (Everett, 2002).

DES is used in another study in order to compare the use of pooled list with scheduled lists. In contrast to scheduled list, pooled lists are an assemblage of undedicated tasks for various workstations. A DES model is built, including the availability of surgeons for appointments that are also dependent on other clinic activities. The results of the paper show that about 30 per cent fewer patients are waiting during weeks when no appointments are available under the pooled-list method (Vasilakis et al., 2007).

Another DES is designed in Wittness – a simulation programme - to surgical departments in a hospital located in Genova, Italy (cf. Sciomachen et al., (2005)). The performance indices are investigated with special focus on wards' productivity in terms of utilisation rate, patient throughput and overruns, resulting in unplanned overtime for staff. Different scenarios are tested to compare the actual time table with initial schedule which uses a blocked booking criterion for weekly scheduling. The model considers a weighted priority rule, which depends on the time waited, pain or organic dysfunction status, disability, and disease. Another scenario to be investigated is the implementation of a pre and post recovery room. It is concluded, that applying the master surgery schedule reduces the waiting list and the number of overruns by about 25 per cent and 10 per cent respectively. While the selection of the shortest processing time rule in comparison to the longest processing time rule reduces the number of overruns by 54 per cent and the total overrun time by 30 per cent, leading to a general reduction of the average utilisation rate (Sciomachen et al., 2005).

An outpatient surgery at the University of Iowa, USA, uses simulation to model their operating room utilisation, where the inputs of the model include different methods to determine when a patient will be appointed for a surgery. Algorithms similar to those applicable to the knapsack problem, like the on-line bin-packing algorithms, are used to consider case durations, lengths of time patients wait for surgery, hours of block time for each day, and number of blocks each week. Scheduling strategies like next fit, best fit, worst fit, and first fit are evaluated. With the evaluation of these strategies it is concluded that a mean waiting time of 2 weeks for treatment is reasonable goal (Dexter et al., 1999).

Productivity improvements at the surgery unit are the major concern of the study conducted at the Kuopio University Hospital (KUH), Northern Savo, Finland. For this study the surgery records of 2603 patients are investigated and used for the DES which included linear regression model as an optimisation strategy. The linear regression model is used to forecast the schedule of the operating theatre and could explain 46 per cent operating time variance. The study recommends a more flexible scheduling policy. For example, if more patients willing to be called for surgery at short notice, then longer fill buffers are a cost effective way to increase output, whereas an increase of queue length for elective patients has a positive effect on productivity (Lehtonen et al., 2007).

At the Children's Hospital of Philadelphia, USA, a study focuses on the determination of the optimum operating room utilisation. Under the investigation of several schedule policy schemes, it is illustrated that a reduced variability of durations of operations increases utilisation, while higher variability allows less utilisation to meet the target for patient delay. To consider these fluctuations it is concluded that the operating room is used most efficiently with utilisation being between 85 per cent and 95 per cent (Tyler et al., 2003).

As stated above the surgical unit is one of the most challenging units for DES within a hospital. The review highlights that DES in combination with scheduling algorithms is a powerful tool to assign both human and physical resources in an optimum solution, which in most cases present a trade off between utilisation and acceptable waiting times.

2.1.3 Review of simulation projects in intensive care units (ICUs)

Intensive care beds are dedicated to those patients that are in life threatening state or need constant surveillance. These patients may require special life supporting aids, special treatment, monitoring devices and high staffing ratios, which are a high cost factor for a hospital. It is not surprising that hospital management is motivated to have "just enough" beds in order to meet patients demand. A typical issue reflects the situation at a typical ICU which is that the random arrival of the emergency patients concludes that it becomes more expensive to guarantee a free bed for all admissions at all times. A small probability is always given of having a sudden rush of emergency patients for which there will never be enough beds (Ridge et al., 1998). Due to high variance of the demand it is either the aim of the hospital management to flatten this variance, or to forecast the demand as accurately as possible to avoid unplanned patient rejection or transferral, which is an undesired measure. The following papers show elegant ways to avoid these measures by applying simulation in different configurations as a precaution planning tool.

A simulation model for the bed capacity planning in Intensive Care is described by Ridge et al., (1998), whose model displays a non-linear relationship between number of beds, mean occupancy level, and the number of transferred patients. The simulation model is based on an analytical queuing model encoded in PASCAL using a 3-phase simulation shell to gain a better understanding of the investigated ICU and to investigate the system in depth. One of the major achievements of the model is the display of the probability distribution of the number of free beds at any particular time of the day (Ridge et al., 1998).

In an ICU of a public hospital in Hong Kong, Kim et al., (1999) analyse the impact on patient welfare and the hospital's cost effectiveness of the admission-and-discharge processes. Queuing and simulation models are built with actual data covering half a year of patient records, to provide insight into the operations management issues. The multiple server model helps to identify bottlenecks and to improve the flow of patients. Further, the capacity usage of the ICU is improved through better communication between surgeons and the unit's administration staff (Kim et al., 1999).

In the following year the authors published another paper which investigates various bed-reservation schemes on the background described above. The previous study is continued and the results are summarised in a classic efficient frontier, which illustrates the area of efficiency of investigated parameters. This provides a useful medium for the ICU administrator, providing a discussion platform which illustrates the rationale behind the chosen bed-allocation system to the surgeons and the ICU physicians. Several strategies are tested which significantly improves the current system: one reduces the cancellation rate of surgeries by 24.6 per cent while patient queuing would increase by 1.2 hours (Kim et al., 2000).

Continuing their optimisation effort of the ICU of a public hospital in Hong Kong, leads to a publication of another study which focuses on the advance-scheduling property for elective surgeries. Daily quota systems are explored with a 1-week or 2-week scheduling window combined with performance implications. A quota system is integrated in the simulation model which is either fixed or flexible in connection with flexible bed allocation. The investigated quota system enables consideration and integration of elective surgeries into the ICU admission process. In conjunction with a flexible bed allocation scheme, it is possible to reduce cancelled surgeries significantly (Kim and Horowitz, 2002).

The following project targets the cooperation of hospitals of the Rijnmond Region, Netherlands, where the hospitals jointly reserve a small number of beds for regional emergency patients. This approach is presented in a mathematical method, while a simulation model used in telecommunications system with multiple streams of phone calls verifies the findings. The project shows the benefits of the cooperation on the overall capacity usage of the participating ICUs. Results show, that cooperation may lead to a reduction in rejected patients, and cancelled operations (Litvak et al., 2008).

The review shows that simulation is on one side used to identify problems, and on the other side used to incorporate solution techniques as for example the quota system applied (cf. Kim et al. 2000). To avoid cancellation of elective surgery and its negative consequences on the welfare of the patient, pooling of resources in conjunction with other hospitals is an option as demonstrated in the Rijnmond Region, Netherlands (cf. Litvak et al., (2008)).

2.1.4 Review of simulation studies in inpatient speciality facilities in hospitals

From the process flow perspective the inpatient speciality facilities are characterized by clients and servers with multiple interfaces. These inpatient specialty facilities, an integrated subset of the hospital, share its properties like uncertainty of patient demand and common human and physical resources. Specialties are, as the name suggests, focussing on one specific area of patient treatment or diagnostic.

An ambulatory care and diagnostic centre like in Central Middlesex Hospital increases the day treatment cases and lowers the bed capacity demand. Functioning like a walk in centre, a lower demand for surgical procedures allows surgeons to focus on severely ill patients and those with complaints. Bowers and Mould, (2005) use computer models to simulate several years of activity in an orthopaedic department to show the effect of the opening of the Ambulatory Care and Diagnostic centre for the Central Middlesex Hospital. The model is built in Simul8 and uses data of the clinic records and implemented scheduling algorithms similar to stochastic knapsack problem are used. Investigating simulation results show that the Ambulatory Care and Diagnostic Centre reduces the overall theatre utilisation by up to 15 per cent (Bowers and Mould, 2005).

The introduction of an acute care unit at the Whittington Hospital, UK, is modelled and simulated with a stochastic model in order to evaluate the optimum rate of acute to non-acute beds. Results show that 60-65 per cent of beds should be reserved for acute care if an intermediate care facility is to be instituted (Utley et al., 2003).

Another specialty analysed with the use of simulation is the catheterization unit at the Maastricht Academic Hospital (Groothuis et al., 2001). Previously the catheterization did not accept any patient after 4 p.m., but with the use of simulations two different scheduling strategies are tested and the resulting effects are analysed. Performance measures are the number of treated patients and the duration of a working day, which identifies the best scheduling strategy that enables 8.05 patients in average to be treated, while 80.5 per cent of the working days finished within eight hours. The results obtained from the simulation illustrate the outcome of each strategy, which enables an easier understanding of how efficiency is achieved (Groothuis et al., 2001).

Another study on a catheterization unit is undertaken, as mentioned above, at the University Hospital Gasthuisberg (Cardoen and Demeulemeester, 2007). The impact of the sequenced surgery on scheduling strategy is shown with the use of DES. It also illustrates that the optimum performing scheduling policy is a trade off between different performance measures; for example, by either allowing a high cancellation rate or having a long overrun time. It is emphasised that DES benefits from, and also for, patient care pathways (Cardoen and Demeulemeester, 2007).

Two specialties, neurology and gynaecology, are investigated with simulation based capacity estimation at the Academic Medical Center in Amsterdam, the Netherlands (Elkhuizen et al., 2007). The simulation consists of a queuing model to provide rapid global insight into the capacity requirements to accomplish a norm of seeing 95 per cent of all new patients within two weeks. Implementing the results frees 14 per cent of unused capacity of the gynaecology and dedicate it to neurology (Elkhuizen et al., 2007).

A family practice healthcare clinic is used for the Visual Simulation Environment (VSE) based on object-oriented DES. The simulation model includes several statistical techniques like batch means, fractional factorial design, simultaneous ranking, selection, and multiple comparisons. Optimized results are obtained with the help of multivariate output analysis, like ranking and selection or multiple comparison procedures. Included in the model to increase performance motivation, the clinics' fictional profit has been linked to patient satisfaction by introducing a financial penalty for each waited minute. This model gives a broad basis for decisions and discussion, especially when the quality of care and patient satisfaction is taken into account (Swisher and Jacobson, 2002).

Another attempt to imply the patient and staff satisfaction is undertaken at a Medical Assessment Unit (MAU) of a general hospital within the UK (Oddoye et al., 2009). In the first step the simulation model is used to eliminate bottlenecks, while the second step considers the patient and staff satisfaction by setting a metric scale in the goal programming method. This study shows that multi-objective decisions arising in the MAU can be handled effectively with the combination of simulation and goal programming (Oddoye et al., 2009).

At the geriatric department of the St. George's Hospital, UK, models are built to forecast the length of stay and the average number of patients in each process state. A queuing system is designed to explain the effect of blockage on the flow of patients, while simulation is used to apply "What-if"-analysis. The effectiveness of internal processes is measured by different constrained simulation configurations. Other statistical measures like idleness, waiting time and cancelled appointments of patients are easily obtained from this model (El-Darzi et al., 1998).

Hospital diagnostic image centres like the magnetic resonance imaging centres are specialties that share the same client groups as hospitals: scheduled outpatients in advance, inpatients that are generated randomly during the day and emergency patients that have to be served immediately. Dynamic priority rules are generated to service and admit patients by using a finite-horizon dynamic programme based on a Markov Chain. The interaction between the strategic appointment scheduling and the tactical capacity allocation is reflected in the optimisation model. It is important to note that the evaluation of the three investigated scheduling policies: 'fill all slots', 'balanced', and 'newsvendor'; of which the last attempts to achieve the most profitable allocation. It is concluded that the policies are significantly influenced by the uncertainty of the durations of diagnostic exams (Green et al., 2006).

Balanced bed utilisation, also an issue for an obstetrics hospital, is simulated with a model based on queuing network analysis. The primary goal is to minimize blocked beds from upstream units within given constraints on bed allocations, while the flow through the balanced system is investigated with DES under the consideration of non-homogeneous effects, non-exponential length of stays, and blocking behaviour. Results show that patient flow is increased by 38 per cent when only 15 per cent more beds were available; these results are implemented in practice (Cochran and Bharti, 2006a).

The appropriate allocation of human and physical resources is also of concern for specialty units within hospitals as it is for the whole hospital. In fact specialties often are required to provide resources that are utilised by other units elsewhere, which increase the dynamics in analysing the system. Uncertainty of patient demand is the common theme and the overall patient demand is a combination of planned scheduled patients, the unplanned inpatients and emergency patients. To find the best combination and trade off, simulation is used to either find the best schedule or the best resource allocation to meet demand. Two studies also include the patient satisfaction into their models: Swisher and Jacobson (2002) include a financial penalty for each minute waited, which would lessen the overall fictional profit, but ensures short waiting times; Oddoye et al., (2009) set a metric scale within their goal programming model by considering the queuing lengths as a measure for the patient and staff satisfaction. These two studies show that in simulation models not only are quantitative outcomes investigable, but also that quality aspects, as experienced by the patient, may be measured.

2.2 Review of simulation studies on emergency departments (EDs)

Emergency departments (EDs) are commonly attached to an acute hospital and should therefore be grouped as a subunit of a hospital within this review. Yet, the special role of the ED, facing the highest uncertainty in demand, is rather outstanding, and thus warrants investigating the ED as a unit of its own sight. EDs represents a major source of admissions to the hospitals inpatient facilities. Patient attendance at EDs is largely random while the allocation of available resources to review and treat patients is generally undertaken by use of a triage system to ease uncertainty. From the hospital management point of view, the ED serves as a gate keeper for uncertain demand by providing urgent patients immediate care and necessary treatment, which lowers their severity and allows a plan able component for the hospital admission for the once unplanned immediate patient demand. Another outstanding, but routinely applied feature of an ED is the flexible response to priority; patients in a severe state need to be treated sooner as patients that are in a save condition. Even though the uncertainty and the flexibility attributes are also shared by the hospital, their levels within the ED are rather outstanding.

A general simulation tool and a guide for developing a simulation tool for ED is based on a study of five different Israeli hospitals (Sinreich and Marmor, 2005). These simulation tools investigate in depth the arrival of patients, illustrated in an arrival model. The overall process flow of the patients laid out with the corresponding similarity values of the different patient process charts. Conclusions, which are focusing on the recent hospital admission policy, suggest that patients are better characterized by type like internal, surgical or orthopaedic rather than by the specific hospital visited. In addition this simulation tool is easy to handle for hospital management and important key performance figures are easily derived (Sinreich and Marmor, 2005).

Another study is undertaken at the Surgical ED at Istanbul University School of Medicine, which recommends new bed capacities to improve the current system. This implemented study makes a twofold contribution to the ED: first, the results guides management in their expansion plans, and second, affects the organizational culture of the department because it shows the importance of computerized process data, which also describes patient pathways (Kuban Altınel and Ulaş, 1996).

An investigation on the impact of the bed occupancy level on to inpatient bed crisis is undertaken with a discrete-event stochastic simulation model at a hypothetical acute hospital in England. Results show that hospitals operating at bed occupancy level of 90 per cent or more are likely to face regular bed crises. Hospitals with a bed occupancy level of less than 85 per cent generally avoid a bed crisis as well as the associated risks to patients. Management should therefore plan interventions on a long term basis to match future demand growth (Bagust et al., 1999).

The Children's Hospital of Eastern Ontario apply DES to quantify and optimize the delivery of primary care through the hospital's ED. Focus is set on waiting time, which is reduced by the implementation of fast track facilities for treating patients with minor injuries. Estimates show that one third of the patient volume is absorbed by the new fast track facility and results of the simulation model show that the average length of stay decreases by 10 per cent (Blake and Carter, 1996).

A combination of the dynamics of the DES model and the static description with role activity diagram is applied to describe the activities in an ED of a Mexican Hospital. This combination enables describing the process flow together with socio-technology issues.

One of the major concerns of this study is to eliminate bottlenecks and the results predict a rise in throughput of 20 per cent. This is achievable by capacity increase and elimination of bottlenecks (Martinez-Garcia and Mendez-Olague, 2005).

The paper with the provocative title: ‘Looking in the wrong place for healthcare improvements: A system dynamics study of an accident and ED’ (Lane et al., 2000) uses system dynamics to simulate the interaction of demand patterns and ED resource deployment. Interfaces with other hospital processes and hospital bed numbers are also considered as well as the impact of variation in output policies. There are two conclusions: first a selective stock-up of resources reduces unavoidable waiting times for patients, and second the reduction of bed numbers in the hospital does not affect waiting times but directly affects the cancellation rate for elective patients for surgery (Lane et al., 2000).

A NHS Walk-in Centre is planned and designed with the use of simulation at the North Mersey Community National Health Service Trust. Simulation results show how a Walk in Centre could be managed alternatively. This paper offers a basis for discussion and suggests changes, for example, the publication of busy times at the centre in a local newspaper in order to reduce the rate of patient arrival at peak times (Ashton et al., 2005).

Measuring crowding in an ED is achieved by Hoot et al., (2008). The theoretical model is validated with patient data from an academic ED, which facilitates a patient tracking system. A sliding-window design validates the model, which ensures separation of fitting and validation data in time series. Measures like the amount of waiting patients, waiting time, occupancy level, length of stay, boarding count, boarding time, and ambulance diversion are used to apply Pearson’s correlation to achieve a forecast for the short term of eight hours (Hoot et al., 2008).

An application of Total Quality Management (TQM) concepts with the help of simulation-animation is undertaken at an ED of Hospital Perea, Puerto Rico. The simulation analysis covers triage, insurance filling, doctor visits, laboratory, x-rays, ct-scan, recovery room, and respiratory therapy. Conclusions specify a list of the recent ED attributes which affects its performance: non-standardized job descriptions, insufficient number of doctors, nurses and equipment to service the demand, backlock of hospital admissions. All these factors interrupt a smooth patient flow (Gonzalez et al., 1997).

Genetic algorithm is combined with simulation in order to optimize the nurses’ schedule at the ED of Show-Chwan Memorial Hospital in Central Taiwan. The simulation model considers the complete flow for the patient through the ED. Genetic algorithms are facilitated in order to minimize the patient queuing time of which the implemented results showed a significant impact on the patient queuing time by an average of 43 per cent. These results increased dramatically the quality of patient care and patient satisfaction (Yeh and Lin, 2007).

EDs are deeply affected by random demand. To manage the flow of patients, simulation has showed itself as an invaluable tool for hospital management as it offers guidance for solving issues related to occupancy level, waiting times and allocation of resources. Relationships to intersecting areas of the ED like common resources with the hospitals are also identifiable, which is comprehensively illustrated by Lane et al. (2000) who vitiate the previous common assumption that a reduction of hospital beds only affects lengths of stay of ED patients due to backlock effects of hospital admission on the ED. By indicating the direct relation between cancellation rate of elective patients and hospital beds, the previous assumption is doubted. Gonzales et al. (1997) apply TQM and animated simulation to identify the overall patient flow as a problem. The importance of identifying issues cannot be underestimated. More quantitative improvement suggestions are made by other authors, like providing the possibility to forecast ED crowding up to the next eight hours (Hoot et al., 2008), or the outstanding decrease of average patient queuing time of 43 per cent by the application of genetic algorithm to simulation (Yeh and Lin, 2007). Considering the quantitative and qualitative improvement potentials as identified above, it can be said, that simulation has contributed as a valuable decision support tool.

2.3 Review of outpatient departments

Although similar to inpatient specialty units within a hospital, outpatient departments differ significantly by their degree of independence. Consultants, nurses, treatment and diagnostic rooms are also provided in an outpatient department, but the intersection with an associated hospital is limited to a certain amount of referral patients. Administration decisions are applicable within the department, without the need for an approval of the hospital management. The following review shows the use of simulation either to improve the patient flow or to find the best scheduling policy.

A general design and development of a DES model, based on the object oriented paradigm (OOP) is described in a study for a physician clinic placed within a physician network. A visual simulation environment to aid illustrating and communicating the findings are presented as results. The development process is well described in this study, including detailed descriptions like the covered patient pathways, data retrieval, and modelling approach. This simulation model allows detailed insights into the mechanisms of a physician clinic, which enriches the decision basis for the decision maker (Swisher et al., 2001).

The effectiveness of an outpatient transfusion centre is investigated by using a methodology that interactively uses system simulation, estimation of target function and optimisation. Multiple servers and facilities are assigned to different services with budget restrictions. Although combining several complex elements, an easy-to-use system is developed with which the manager get the possibility to evaluate the outcome of certain scenarios. The focus may either be set on the performance or quality level, each leading to different recommendations / results (De Angelis et al., 2003).

A rather enthusiastic project is reported by the vascular-surgery outpatient service at Good Hope Hospital that develops a software tool named as Care Pathway Simulator (CPS). Routing multiple patients differently through the patients care pathways, the CPS predicts the behaviour of the complex system. Thus, the CPS enables the identification and elimination of bottlenecks to increase the efficiency of capacity usage. This project results in a 40 per cent increase of capacity usage, due to an optimized booking schedule. This increase is achieved without any additional resources (Dodds, 2005).

A network of outpatient clinics is investigated at Calgary Laboratory Services, Canada. The objective of this study is to analyse the effect on the patient demand, if the number of laboratory facilities would be downsized from 25 to 18, 12, or 6 facilities respectively. A discrete event simulation model is developed to forecast the benefits of pooling and to illustrate the best service provision. Results suggest 18 facilities which are implanted in practice. Observing the outcome of the implementation shows a surprising oscillating effect on patient demand, which is then described by system dynamics. It is concluded that system dynamics made a significant contribution to complete the simulation model in order to explain the overall system behaviour (Rohleder et al., 2007).

Moving away from the general model of an outpatient department, the following study focuses on the appointment scheduling of doctors. For this purpose a simple closed-form heuristic is designed for setting job allowances for up to 16 homoskedastic and equally-important customers. The results show, that the heuristic performs an average within 0.5 per cent of the cost of the optimal policy (Robinson and Chen, 2003).

Another simulation model to test various appointment schedules is applied to the Ear, Nose and Throat (ENT) outpatient department near London. This model is built on the feedback of consultants and experienced staff. The results show, that if clinics would start promptly, then, on average, 15 minutes of patient wait is saved. Furthermore, the analysis of the schedules show that grouping patients into large blocks should be avoided to gain another 8 minutes on patient wait (Harper and Gamlin, 2003).

The next case-study focuses on the use of simulation in order to shorten the out-patient queues of a dermatology outpatient department at a local hospital at Chia-yi in Taiwan. Applying ‘what-if’ scenarios to the simulation model show a remarkable increase to performance if an extra session on Monday afternoon is added. Once implemented the length of stay reduces by 47 per cent, only 3 per cent of patients had a LoS of more than 1.5 hours, the maximum queue length is reduced to a third of its original value, and the utilisation of physicians is reduced 78 per cent (Huarng and Lee, 1996).

The next study aims to minimize the patient queues at the Gero prefectural hospital in Gifu, Japan by using DES in order to test four different scheduling strategies: B2 (Baily), Rising, 15MIN, and SPTBEG. Conclusions show that the SPTBEG rule is best for reducing waiting time, while 15MIN rule is the best to reduce physician idle time, therefore a hybrid combination of 15MINRising would be most suitable (Wijewickrama, 2006).

Applied simulation in outpatient departments has in general two beneficial effects: first to gain a better understanding of the mechanisms operating within such a complex system, and second to apply ‘what-if’-scenarios to the model without interfering with the actual running system. Scenarios can be run, for example, to determine the best performing schedule rule (Wijewickrama, 2006). The other reviewed papers also make wide use of applying ‘what-if’-scenarios, due to its easy application as an optimisation strategy, especially when combined with visual interaction (Swisher et al., 2001). Simulation played an important role, especially when designing or instituting health care facilities. Downsizing, but still providing the essential services, is an issue which has been resolved by Rohleder et al. (2007), who evaluates the optimum amount of laboratory facilities to serve a region.

2.4 Review of simulation applied in demographic health care

Providing health on a large scale is of public concern and one of the essential governmental tasks. Question arise how to address or reach each potential patient in order to provide the appropriate service to individual needs. Not considering the provision on a large scale can cause demographical damage to the society and to the individual which might be avoidable. The costs of prevention plans are also a concern, beginning with the encouragement of healthy living and ending by providing health services in case of a large catastrophic events. Provision of health is reviewed on several fields within this review, like transplantation policies, forecasting of costs for certain diseases like HIV, or facilitating access to health services for the general public. Ethical issues have also to be considered because of the impact of decisions taken.

The study of the winter bed crisis of British hospitals which occurred every year two weeks after Christmas is published in 2001. Potential causes are assumed to be the bad weather, influenza, older people, geriatricians, a lack of cash or nurse shortages. Another potential source could be that beds within the hospitals are blocked due to lack of social services for discharge hospital patients during the Christmas period. In order to investigate the real causes of the winter bed crisis problem depicted to a DES model, using its extensive 'what-if' capabilities. The results hypotheses that staff leave and public holidays is a possible explanation of the winter bed crisis and emphasis that influenza can be excluded as a reason (Vasilakis and El-Darzi, 2001).

A whole system review of emergency and on-demand health care is conducted in Nottingham, England. This study aims to investigate the overall provision of health services within a region and to forecast the effect of public growth. This simulation is constructed like a stock-model, which is populated with current activity data, in order to simulate patient flows and to identify system bottle necks. Results highlight, that without intervention, or investments to increase capacity, the governmental target of 82 per cent bed occupancy will not be achieved due to current growth rate (Brailsford et al., 2004).

Another study which looks at the catchment area of a hospital is applied to a public hospital in Hong Kong in order to plan the supply and demand matching of public hospital beds for the next 6 years ahead. Hospital location and service allocations are addressed as planning issues in addition to redistributing existing services as well as instituting new services. A framework for guidance purposes is given within this study, which also includes the case study applying a mathematical model. Various possibilities to balance the local demand are tested and three benefits of the model are listed: first the use as an elevator, which means that the model can serve as an analytic description of different scenarios to allocate hospital and services, second the use as a predictor, and third the use as a decision support system (Chu and Chu, 2000).

Centralization is known to be an effective procedure to benefit from pooled resources. However, in practice centralization is difficult to accomplish as improvements to the overall performance may be disadvantageous to some entities involved. A simulation based methodology studies the impact of equipment pooling at a group of local community service centres in the Montreal (Canada) region. The results reveal that similar levels of overcapacity of each centre are more effective than minimum stock, maximum contribution or maximum dept rules considering the overall reduction in costs without penalising any of the partners in the pooling process (Pasin et al., 2002).

DES is also used to test the effect of introducing a new range of services termed 'Intermediate Care' which offers alternative options for older patients. This case study determining system capacities, investigates potential care pathways after discharge from hospital with a simulation model. One aim of this model is to estimate the likely associated reimbursement costs. The implementation of the pathway demonstrates that this simulation model has been of great value for the planning and design of the services, which helped throughout the whole institutionalization (Katsaliaki et al., 2005).

Another study providing health supporting devices like semi-automated early defibrillators (AEDs) for the area around Vienna was undertaken for the Austrian Red Cross. To gain insight into the relationships and mechanisms, an integer programming model analyses the cost effectiveness. The aim of the study is to set off the costs of this intervention with the gained quality-adjusted life-year (QALY). Constraints to the model involve the costs that include the acquisition, maintenance, training costs, as well as the hospitalization costs, while considering the improved survival and quality-of-life contributed beneficially to the model. Results show that the equipping all ambulances is cost effective. In addition, the results suggest an introduction plan which specifies which region should be equipped first with AEDs (Rauner and Bajmoczy, 2003).

Modelling catastrophic scenarios like the provision of health services by hospitals in an earth quake event is the background for the investigations undertaken by Paul et al., (2006). Simulation and exponential functions are used to model the hospital network, which allows representing the transient patient waiting times during a disaster. Several live saving analyses, processed in real-time, are achieved by the developed model: first there is the capacity estimation of hospitals of various sizes and capabilities and second, it allows priority-based routing to guide patients based on the severity of injuries and places the patients that are requiring critical care in appropriate queues based on their remaining survivability time (Paul et al., 2006).

An estimation of future costs for the treatment of diseases is undertaken by Harper and Shahani, (2003) in Mumbai, India. This mathematical model is based on Markov Chains and Semi Markov Chains, which considers public data, compiled by the WHO. The model helps quantifying likely funds required for HIV care over a ten year planning horizon (Harper and Shahani, 2003).

Transplantation policies are also a subject which is modelled in a DES developed (Roderick et al., 2004). This model uses a patient-oriented simulation technique software that considers the changing modalities of individual simulated patients for the next 30 years into the future. The results suggest raising the funding for the renal replacement therapy provision to meet future demand (Roderick et al., 2004).

Another study emphasising of effective allocation of transplant organs is undertaken by Ratcliff et al., (2001). Their research considers the distribution policy of liver organs and includes fairness aspects into their simulation model. For evaluation purposes the model is based on demographical data. A long discussion section includes the issues on identifying fair donor policy for liver transplant (Ratcliffe et al., 2001).

A new method to incorporate human behaviour in modelling screening processes is applied by Brailsford and Schmidt, (2003). Their approach uses ideas from the discipline of health psychology in order to simulate more accurately patients attendance behaviour compared to the common standard approach of simple random sampling of patients (Brailsford and Schmidt, 2003).

The prevention of retinopathy is one contribution which is studied by applying several different DES models by Davies et al., (2003). Results show that large scale screening of pre-treatable retinopathy is cost effective and initial results show that costs may be reduced by one third (Davies et al., 2003).

Another study, concerned with the screening of retinopathy, is undertaken (Harper et al., 2003) in India. In order to guide the screening of patients, they are divided into several risk groups by applying a CART analysis, which is then used as an input for the simulation model. The classification aids to identify patients groups for early screening in order to diagnose patients when they are in a pre-treatable state. Results indicate a significant amount of patients could be prevented from developing retinopathy (Harper et al., 2003).

The reviewed papers on the demographical health provision showed how to channel funding in the most effective way, which leads to a greater common good, and higher sustainability of investments. If prevention is successful, it does not only add years of quality live for the individual, it also contributes to the society. Simulation can contribute on either setting the basis for necessary discussion on policies or to guide the decision makers in effective measures.

2.5 Review of simulation applied in health care supply chain environment

The following review presents papers cover the immediate environment for health care providers. Yet thus studies share common features like the uncertainty and variability of demand like in laboratories, hospital elevator systems, blood platelet production facilities, and car parks for hospitals.

A biochemistry laboratory at hospital in Ysbyty Gwynedd, North Wales faces an annual cumulative workload increase of 20 per cent. DES is used to find an appropriate response as well as replacement strategy and to investigate the effects of increased workload. The conclusions show that investments have to be considered timely and be balanced in order to be most beneficial. Bottlenecks are avoided by choosing integrated solutions and by early adjustment of work practices (Couchman et al., 2002).

Blood platelets production is dependent on the supply of donors and product is highly perishable. Additionally the demand for blood platelets is highly variable and uncertain. To minimize the ‘spillage’, a combined Markov dynamic programming and simulation approach is used. Results report that the present blood bank outdating of 20 per cent is unnecessarily high and could well be 3 per cent. In a particular case reflecting the situation in the Netherlands outdating could be even about 1 per cent (Haijema et al., 2007).

A hospital lift system simulator is developed and tested at three different hospitals in Hong Kong by Chu et al., (2003). As a result, a visual simulation-based decision support system is presented that allows integrating any zoning policy at any given hospital design (storey, type, complexity). Lift manufacturers are enabled to test certain lift implementations and investigate certain discrepancies, while hospitals may consider their current lift configuration (Chu et al., 2003).

The supply of car parking spaces is being investigated at the Gifu governmental hospital, Japan, by using an animated simulation model to determine the optimum level of parking spaces. This model is based on hospital records as well as on observations of visitor behaviour. Results suggests to decrease the actual long-term parking time and to implement additional policies to increase the average patient cycle time. An implementation of a machine numbering space system is recommended, which would provide better service at lower cost (Wijewickrama, 2004).

Uncertainty and variability of demand or supply is not only directly affecting health care and its service, these properties are also inherited to the service or production involved with health care facilities. To find solutions and develop recommendations for this field, simulation has been applied successfully either to find an appropriate investment plan, to avoid unnecessary spillage, or more generally to act as a decision support system tool.

3. Discussion on implementation issues

The implementation of simulation results is the final, yet may be hardest, challenge. Summarizing the above publications during 1995 to 2008, 30 per cent of their results are identified to be implemented, compared to 8 per cent which is reported by Wilson (1981) who reviewed about 200 papers published until 1980. This significant increase in the implementation ratio shows a higher acceptance for simulation as a solution technique for health care. Further recommendations for simulation modellers to overcome implementation issues are given by Wilson (1981), Lowery et al., (1994), and Jun et al., (1999) within their discussion section:

- Recognition for the necessity of a change to the existing system
- Total commitment of the modeller
- Availability of data
- Close communication
- Credibility of the model
- Response to deadline

These key indicators given above, extracted from the discussion sections, do not guarantee a successful implementation. External reasons, caused by an unforeseen overall system change, may obsolete the necessity for the certain simulation study. One significant barrier is identified in Lowery et al., (1994): the terminological language gap between the modeller, that comes from an engineering background and the manager with the health care background. For example, if the modeller speaks of an increase of efficiency, it could be misinterpreted as a higher workload by staff. The overall contents of the implementation issue and its barriers are certainly applicable today, looking in the future, implementation reservations may be reduced because of the higher acceptance of applied computer technology. Simulation is a common approach for solution finding in military, manufacturing and logistics (Baldwin et al., 2004) and once health care providers will adopt this attitude.

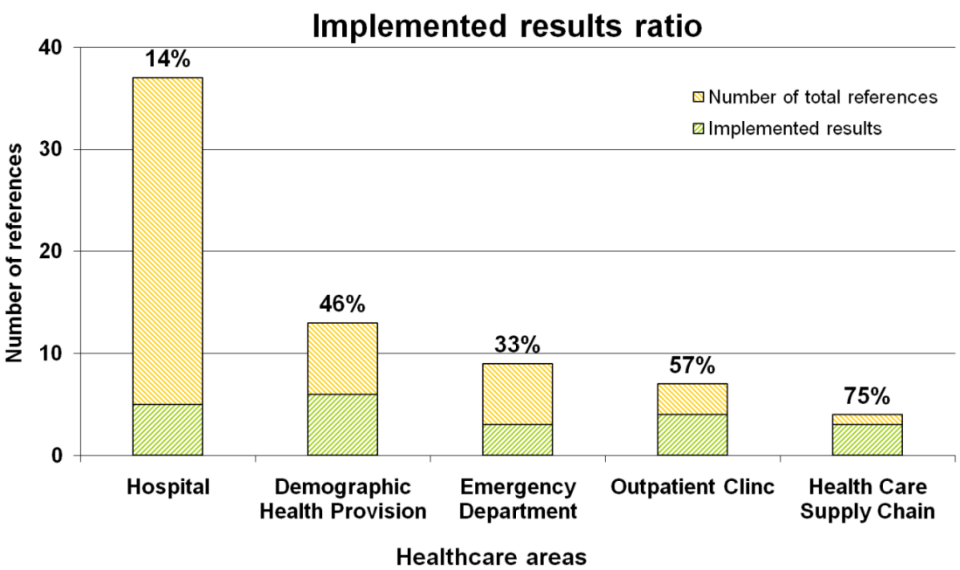

Figure 4: Showing the number and the percentage of projects that implemented their results

Focusing on certain healthcare areas it can be observed that the highest implementation rate is in the health care supply chain environment with three out of four, while the lowest is in hospitals with 14 per cent. It can be argued that first, 3 out of four is definitely not representative, but on the other hand, these facilities resemble manufacturing more thus are more likely to adopt. In addition, hospital management is more restricted because it needs to ensure the safety of their patients. Figure 4 shows the implementation ratio for each health care area.

4. Conclusion

A review of literature covering simulation applied in healthcare and its constituent areas is presented in this paper with a focus on the last decade. Due to the large volume of publications over the past decade, the review offers a reference work, which summarises the simulation along their application areas to facilitate a quick reference guide. While, this review cannot cover all publications of the last decade, it can be considered as an extension of the major survey undertaken by Jun et al., (1999).

Although application areas of simulation differ within health care, common features are the variability and uncertainty of demand, as well as the involvement of human and physical resources in various tasks, which leads to a high level of complexity. Under these conditions, focusing the simulation effort on certain sectors at a time appears reasonable for categorization within this review.

In the fore coming studies of health care operations various types of simulation are encountered: DES is the most common, because it is possible to integrate other solution techniques like mathematical programming, various optimisation strategies, scheduling, and animation. Applying 'What-if'-questions to DES is a favoured approach to understanding the mechanism impacting on the complex system. Other simulation approaches are based on stochastic simulation or apply mathematical models to retrieve results.

It is observed that the application of object orientated simulation modelling is increasing, which either caused a necessity to adapt to the vast complexity of the facilities or the availability of sophisticated software packages for an object oriented approach. These packages allow a flexible modelling with multiple levels of details are a promising approach to reduce complexity in business process design (Baldwin et al., 2005) which may lead to even more applications in the health care sector.

Considering rising implementation rate since 1980 and the potential benefits of simulation offers a very promising outlook for simulation applied in the health care sector. Overcoming the remaining implementation challenge is one of the major tasks for modellers in health care, although the recent implementations are promising.

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